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Vulnerability, good governance, or donor interests? The allocation of aid for climate change adaptation

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ABSTRACT

Developed countries provide increasing amounts of aid to assist developing countries adapt to the impacts of climate change. How do they distribute this aid? While donors agreed to prioritise "particularly vulnerable" countries, we know from the general aid allocation literature that donors (also) use aid as a foreign policy tool to promote their own economic and political goals. In this paper, we analyse data on bilateral adaptation aid from 2010 through 2015 to assess to what extent adaptation aid is provided in response to recipient need (that is, vulnerability to climate change impacts) as opposed to recipient merit (that is, good governance) and donors' interests. In contrast to previous research, we find that donors partly take into account vulnerability to climate change. Countries that are physically more exposed to climate change tend to be more likely to receive some adaptation aid and also receive more adaptation aid per capita, as do poorer countries, small island developing states and—to a lesser extent—least developed countries. Countries with lower adaptive capacity, however, do not receive more adaptation aid; instead, donors reward well-governed countries with adaptation aid as well as use adaptation aid to promote their own economic interests. Furthermore, adaptation aid flows very closely follow general development aid flows. The extent to which adaptation aid is new and additional thus remains unclear.
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1. Introduction

Certain climate change impacts are no longer avoidable; adaptation—"the process of adjustment to actual or expected climate and its effects" (IPCC, 2013, p. 1758)—is hence urgently needed, and nowhere more so than in the Global South. Developing countries, while having contributed the least to global greenhouse gas emissions, bear the brunt of climate change impacts, and at the same time have the least resources to cope and adapt. Recognising this "double injustice", developed countries agreed in the 1992 United Nations Framework Convention to Climate Change (UNFCCC) to assist "particularly vulnerable" developing countries to adapt to climate change (UNFCCC, 1992, Article 4.4). At the 2009 Copenhagen Summit, developed countries confirmed this commitment and put forward concrete numbers for the first time. Beyond US$30 billion so-called fast-start finance for the period 2010 through 2012, developed countries pledged to "mobilise" US$100 billion in "new and additional resources" every year for both mitigation and adaptation in the Global South by 2020 (UNFCCC, 2009, Decision 2/CP.15, para. 8). The Paris Agreement repeated this 100-billion-target and specifically called on developed countries to "significantly increas[e] adaptation finance" (UNFCCC, 2015, Preamble, para. 114).

Adaptation finance, much more so than mitigation finance, is largely drawn from public aid budgets (Khan & Roberts, 2013). While this raises questions regarding the additionality of adaptation finance to regular development assistance (a point highlighted by vulnerable developing countries), there are clear synergies between adaptation and development (Ayers & Abeysinghe, 2013; Ayers & Huq, 2009). We focus on bilateral development aid targeting adaptation, or adaptation aid, which comprises the largest share of global adaptation finance (Ayers & Abeysinghe, 2013; Weikmans, 2016).

Who receives bilateral adaptation aid? In principle, there is widespread agreement in policy and academic discourse that those "particularly vulnerable" to the adverse effects of climate change should be prioritised (Barr, Fankhauser, & Hamilton, 2010; Duus-Otterström, 2016; UNFCCC, 1992, 2009; van Renssen, 2011). In practice, research of development aid as well as adaptation aid suggests that donors use aid to further their own economic and political interests as well as to reward recipients for good

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governance and "good" (economic) policies (e.g. Alesina & Dollar, 2000; Berthélemy, 2006; Clist, 2011b; Robertsen, Francken, & Molenaers, 2015; Robinson & Dornan, 2016; Younas, 2008).

Here, we test various models of aid allocation. We assess to what extent donors allocate adaptation aid to countries that are vulnerable to climate change (that is, based on recipient need) or to countries that are of economic or political interest to the donor (that is, based on donor interests). We also test whether recipient merit plays a role in adaptation decisions, given the potential for institutions and policies to facilitate effective adaptation. Unlike previous studies, our analysis uses a dyadic dataset covering adaptation aid flows from 2010 through 2015 across all donors and all recipients reported in the OECD Creditor Reporting System. Following Cragg (1971), we use a two-stage model so as to distinguish between the decision to provide adaptation aid to a recipient country (the selection stage) and the decision as to how much aid is distributed to those selected recipient countries (the allocation stage). In line with previous studies, we find that donors take into account their own (economic) interests as well as recipients' governance when allocating adaptation aid. In contrast to previous studies, we further find that donors also consider vulnerability, notably the physical component of vulnerability. Countries that are physically more vulnerable to climate risks are more likely to receive adaptation aid and also tend to receive higher levels of adaptation aid per capita. Finally, adaptation aid flows closely follow overall development aid flows. To what extent support for adaptation is thus new and additional to official development assistance, as agreed internationally, is questionable.

2. Literature review and expectations

A large and growing literature examines how donors allocate their development aid. McKinlay and Little (1977) and Dudley and Montmarquette (1976) were the first to distinguish between two different models of aid allocation: recipient need or economic assistance on the one hand, and donor interests or foreign policy on the other. According to the recipient need model, donors provide aid mainly to alleviate poverty in recipient countries, driven by "the simple desire to help the less fortunate" (Dudley & Montmarquette, 1976, p. 132). In contrast, according to the donor interest model, donors use aid instrumentally to promote their own economic, political or security interests. These two models lead to divergent expectations about which countries receive more aid. While we would expect that poorer countries receive more aid in a recipient need model, it is countries that are economically or politically important, for instance large trading partners or political or military allies, that receive more aid in a donor interest model.

In the 1990s, a third model of aid allocation was added: recipient merit. According to this model, donors provide higher levels of aid to recipients with "'good" institutions and policies in place. There are two reasons donors might provide higher levels of aid to countries with 'good' institutions and policies: (i) as a reward or way of incentivising the replication of such policies or institutions, or (ii) for the pragmatic reason that aid is considered more effective in well-governed countries and in 'good' policy environments (Berthélemy, 2006; Burnside & Dollar, 2000). While there is debate regarding what should constitute "good" institutions or policies, the aid allocation literature has generally adopted existing measures produced by the World Bank (the World Governance Indicators) and various think tanks when testing this model (Freedom House and Heritage Foundation, for example).[1]

[1] These tend to value democratic institutions, political stability, control of corruption, rule of law, and perceptions about the effectiveness of government and regulation.

A large and growing literature has tested these various determinants of aid allocation for overall development aid flows (e.g. Berthélemy, 2006; Clist, 2011b; Hoeffler & Outram, 2011), and increasingly also for specific aid flows, including 'green' or environmental aid (Hicks, Parks, Robert, & Tierney, 2008; Lewis, 2003) and aid for climate change mitigation (Halimanjaya, 2014). Another strand of research, often game theoretical, focuses on allocation of funding across sectors and in particular examines the ideal distribution of climate finance between adaptation and mitigation (Bréchet, Hritonenko, & Yatsenko, 2013; Buob & Stephan, 2013; Eyckmans, Fankhauser, & Kverndokk, 2016).

In the context of adaptation, recipient need means not only poverty but vulnerability to climate change: the more vulnerable a country is to the adverse effects of climate change, the more it needs to adapt, and the more support with adaptation it should receive. However, identifying vulnerable countries is not straightforward (Klein, 2009). The IPCC defines vulnerability as "[t]he propensity or predisposition to be adversely affected" (IPCC, 2013, p. 1758) and emphasizes two key dimensions of vulnerability: sensitivity, or physical predisposition to be affected, on the one hand, and lack of coping and adaptive capacities on the other (Field et al., 2012; IPCC, 2013, p. 1775). A range of indicators have been developed to quantify and compare the level of physical vulnerability to climate risks of different countries (DARA & Climate Vulnerable Forum, 2012; Germanwatch., n.d.; Guillaumont, 2013; Kaly, Pratt, & Mitchell, 2004; Moss, Brenkert, & Malone, 2001; ND-GAIN., n.d.). Some indicators also include adaptive capacity, although it is contested how adaptive capacity can be measured, given the breadth of the concept which includes aspects such as poverty, inequality, education, or infrastructure (Brooks, Adger, & Kelly, 2005; Fankhauser & McDermott, 2014; Yohe & Tol, 2002). Not surprisingly, all indicators of vulnerability have been criticised for conceptual, methodological and/or empirical flaws (Füssel, 2010). Measurements of vulnerability, especially at the national level, inevitably involve political judgement (Barnett, Lambert, & Fry, 2008).

Regardless of the difficulties involved in measuring vulnerability, many authors argue for prioritising the most vulnerable countries from a normative point of view (Duus-Otterström, 2016; Grasso, 2010a, 2010b)—in line with the UNFCCC principles and agreements (UNFCCC, 1992, 2009, 2015). To what extent are vulnerable countries prioritised in practice? Several studies empirically trace the geographic distribution of adaptation funding, for subsets of donors (Betzold, 2015) or of recipients (Robertsen et al., 2015; Robinson & Dornan, 2016), at the aggregate (Betzold & Weiler, 2017) or subnational level (Barrett, 2014, 2015), and for multilateral funds (Persson & Remling, 2014; Remling & Persson, 2015)—but not for all donors and all recipients at the dyadic level as we do in this paper.

Previous studies find only limited evidence that countries or communities that are more vulnerable receive more adaptation aid. If vulnerability has an influence, it is physical sensitivity rather than socio-economic adaptive capacity that is positively related to adaptation aid. Barrett (2014) for instance finds that high levels of physical vulnerability, as well as donor interests, drive adaptation aid distribution across subnational districts in Malawi. In contrast, socio-economic vulnerability is *negatively* related to adaptation aid. He thus concludes that "[t]he poorest, most marginalized, and climate vulnerable districts receive the least adaptation finance within Malawi" (Barrett, 2014, p. 131; see also Barrett, 2014, 2015). Studies that assess how the multilateral Adaptation Fund distributes its funding reach similar conclusions (Persson & Remling, 2014; Remling & Persson, 2015; Stadelmann, Persson, Ratajczak-Juszko, & Michaelowa, 2014). Vulnerability does not seem to be a criterion; rather, the Adaptation Fund approved "projects from high-income and less vulnerable countries with high

absolute economic saving" (Stadelmann et al., 2014, p. 116). In contrast, Betzold & Weiler (2017) find that physical vulnerability matters; more exposed and sensitive countries tend to receive more adaptation aid from all donors combined. Robinson & Dornan (2016) similarly find a positive relationship between vulnerability and adaptation aid, but not for the group of SIDS.

What are other factors that explain how adaptation aid is distributed beyond vulnerability? The findings for donor interests are surprisingly mixed. Donor interests seem important for the subnational distribution of funds (Barrett, 2014) as well as for individual donors (Betzold, 2015). Overall, however, it is unclear that adaptation aid flows for recipient countries are driven by colonial ties, trade and geographical distance (Robertsen et al., 2015; Robinson & Dornan, 2016). Additionally, the strong relationship between overall development aid and adaptation aid (Nakhooda et al., 2013) suggests that donor interests may well play a role in adaptation aid allocation, given the established relationship between donor interests and the allocation of development aid (Alesina & Dollar, 2000; Berthélemy, 2006; Clist, 2011b; Hoeffler & Outram, 2011; McKinlay & Little, 1977).

Most studies find a relatively strong and robust relationship between recipient merit and adaptation aid: countries that are democratic and well-governed consistently receive higher levels of adaptation aid (Robertsen et al., 2015; Robinson & Dornan, 2016). Recipient merit, in an adaptation context, is hard to disentangle from vulnerability. Well-functioning institutions are better positioned to facilitate adaptation, reducing the vulnerability of populations in those countries. The recipient need and recipient merit models therefore lead to contrasting expectations on adaptation aid levels. Poorly governed and hence more vulnerable countries may need more adaptation assistance, but aid in such contexts may be less effective—and donors reluctant to reward 'poor' policies (Füssel, 2009, p. 18f).

Building on the theoretical and empirical research on (adaptation) aid allocation, we expect that the three determinants of aid allocation—recipient need, recipient merit, and donor interests—influence the distribution of bilateral adaptation aid. Our hypotheses reflect these three determinants and further distinguish between physical vulnerability and adaptive capacity:

H1a. The more physically vulnerable a country, the more adaptation aid it should receive.

H1b. The lower a country's adaptive capacity, the more adaptation aid it should receive.

H2. The better governed a country, the more adaptation aid it should receive.

H3. The more relevant a country—economically or politically—to a donor, the more adaptation aid it should receive from that donor.

Since adaptive capacity (a dimension of vulnerability) and good governance (a proxy for recipient merit) are linked, we have contrasting expectations on measures of governmental quality: If we see a *positive* relationship between measures of governmental quality and adaptation aid, we can interpret this as evidence for recipient merit: donors prefer to allocate adaptation aid to well-governed countries where the impact of their aid is presumably larger, despite this also meaning that adaptive capacity in these countries is higher. If in contrast we see a *negative* relationship between measures of governmental quality and adaptation aid, we can interpret this as evidence for recipient need: donors acknowledge that poor governance implies lower adaptive capacity and hence higher vulnerability, and provide larger amounts of adaptation aid to help such countries deal with the impacts of climate change, despite this also meaning that recipient merit in these countries is lower.

In this way, we can examine the influence of adaptation capacity (H1b) and good governance (H2) on the allocation decisions of donors—notwithstanding the fact that the two are linked. We can also examine the vulnerability hypotheses (H1a and H1b) in isolation, given that most of the variables that comprise vulnerability (H1a and H1b, including half of those that comprise adaptive capacity or H1b), do not overlap with good governance.

3. Data and methods

3.1. Dependent variable: adaptation aid

To test our expectations, we compiled a dyadic dataset of bilateral adaptation aid from all OECD donors between 2010 and 2015 based on project-level aid data from the OECD Creditor Reporting System (OECD, 2016). Since 2010, donors need to identify projects where adaptation is the principal (i.e., main) or a significant (i.e., not the main, but still important) objective, using the Rio Marker for adaptation (OECD, 2011).

The OECD data are not without problems as donors tend to over-state the adaptation relevance of aid projects (Donner, Kandlikar, & Webber, 2016; Michaelowa & Michaelowa, 2011) yet they are the most comparable and comprehensive data available on adaptation aid. To minimise problems of over-reporting and over-estimation of adaptation aid, we report results for principal adaptation aid only—that is, projects where adaptation is the main objective—since over-reporting seems less prevalent for principal adaptation aid flows. We also construct a variable using both principal and significant adaptation aid, but we discount significant aid by 50% as is commonly done by donors when these report their climate finance commitments (AdaptationWatch, 2015).

To compute our dependent variables, principal adaptation aid per capita and principal and discounted significant aid per capita, we aggregated all principal and all significant adaptation aid flows from one donor to the same recipient in a single year. When no adaptation aid between a donor and a recipient country was recorded, we coded the adaptation aid flow for the year in question as zero. For the first dependent variable (principal aid only) we then calculated per capita aid figures for each donor-recipient pair, making use of the yearly summated principal aid flows and the World Bank's total population figures provided in the World Development Indicators (WDI) (World Bank, 2016a). The same procedure was applied to the second dependent variable, but the basis for the per capita calculation was the sum of all principal aid flows plus 50% of significant aid flows from a donor to a recipient in a given year. Overall, we coded 23,406 entries over the five-year time horizon of the study in this manner. Finally, because both adaptation aid variables constructed this way are heavily skewed, we transformed them using the natural logarithm.

3.2. Measures of physical vulnerability

We expect vulnerability to climate change to be a key driver of adaptation aid allocations decisions. As explained earlier, vulnerability has two dimensions: physical predisposition to climate risks on the one hand, and lack of adaptive capacity on the other. Our first set of independent variables are hence three vulnerability indices that measure physical predisposition to climate risks. We expect a higher level of adaptation aid flows as vulnerability (in terms of physical vulnerability) increases. As the three indices all measure physical vulnerability directly and are therefore very

similar to each other, we use them separately, with each model only including one measure of physical vulnerability. We now briefly discuss the three measures in turn.

3.2.1. ND-GAIN exposure

First we use the exposure variable provided by the Notre Dame Global Adaptation Index (ND-GAIN) to capture vulnerability (ND-GAIN., n.d.). This variable is particularly useful for our purpose, as it directly captures physical exposure to climatic changes of countries through measures such projected change in temperature, precipitation or agricultural yield, or land under 10 meters above sea-level. It is thus not connected in any way to other socio-economic variables that we also include in our models (such as GDP per capita as a measure of adaptive capacity, see below).[2] Thus, using this variable avoids potential collinearity problems. The variable is time-invariant, and higher values of the variable indicate higher vulnerability levels. We therefore expect to find a positive relationship in line with H1a.

3.2.2. SVCCI

As a second measure of vulnerability we utilise the Index of Structural Vulnerability to Climate Change (SVCCI). This index focuses on risks from physical shocks and includes measures such as rainfall or temperature stability (Guillaumont & Simonet, 2011). As this index strongly focuses on the physical dimension of climate vulnerability and does not consider the socio-economic dimension (Guillaumont, 2013), it is very useful for our purpose. Higher values are indicative of higher vulnerability levels and we again expect a positive association with adaptation aid.

3.2.3. CRI

We also include the Climate Risk Index (CRI) provided by Germanwatch in the statistical models (Germanwatch, n.d.). The CRI focuses on annual weather patterns and the loss to humans and the economy that climate-related natural disasters such as storms, droughts or floods cause. Natural disasters have been shown to influence aid allocation in the short-term (Becerra, Cavallo, & Noy, 2014), which is why we include this measure in the analysis, even though short-term weather patterns are not a good way to capture long-term climate and adaptation finance needs of developing countries. It is important to note here that our analysis considers only the impact on adaptation aid; (short-term) recovery assistance provided in the wake of a natural disaster is different to (long-term) adaptation assistance, and is not the focus of our paper. Germanwatch reports CRI data annually, and as such, this measure is lagged by one year.[3] The variable is inverted, so that higher values indicate more vulnerability. Accordingly, we expect to find a positive effect on adaptation aid in the statistical models, consistent with H1a.

3.3. Measures of adaptive capacity and governmental quality

The second dimension of vulnerability is adaptive capacity. As discussed earlier, adaptive capacity has many drivers, and disentangling adaptive capacity from good governance is difficult, as strong, well-working institutions also help countries to better cope with the challenges of climate change. We therefore discuss how we operationalize these two concepts jointly in this section.

We include four measures of adaptive capacity, which we describe in detail below. Two of these—governmental quality and ND-GAIN adaptive capacity—are also measures of good governance.

3.3.1. GDP per capita

Countries' financial resources are captured by per capita GDP for recipient countries, and are taken from the WDIs at 2010 constant US$ (ND-GAIN, n.d.). The data are lagged by one year and log-transformed. We also include a squared GDP per capita term to model non-linear effects, following standard practice from the development aid literature (see e.g. Alesina & Dollar, 2000). The idea behind modelling GDP per capita this way is that the poorest countries potentially receive relatively little funding, as they are be unable (or perceived to be unable) to absorb large amounts of aid. Yet once GDP rises beyond a certain level, countries are increasingly able to deal with adaptation challenges domestically—i.e. their adaptive capacity increases—and adaptation aid is expected to decline again. Thus, our expectation is to find a positive linear and a negative quadratic coefficient.

3.3.2. Vulnerability dummies

We include three dummy variables for countries that have been recognised as "particularly vulnerable" to climate change, namely least developed countries (LDCs), African countries, and Small Island Developing States (SIDS). These countries are seen as highly vulnerable because they lack adaptive capacity and—particularly in the case of SIDS—are strongly exposed to climate risks. Since these categories are not mutually exclusive, countries may belong to more than one of these groups. However, the differences between the dummies are large enough for this not to be problematic from a statistical point of view. We do not pool these three country dummies into a single variable as donors may treat the three groups of countries differently. We expect the coefficients of all three dummies to be positive, given our expectation that more vulnerable countries will obtain more adaptation aid, and in light of the international community's acknowledgement of the vulnerability of these country groupings (UNFCCC, 2009, 2015).

3.3.3. Governmental quality

Governmental quality of recipient countries is measured using the World Bank's Worldwide Governance Indicators (WGIs) (World Bank, 2016b). We aggregated all six main indicators (voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption), giving equal weight to each indicator. In the statistical models the data are lagged by one year. From a recipient merit perspective, higher governmental quality signals that the recipient is better able use funds adequately, which should lead to a positive relationship with adaptation aid. From a recipient need perspective, however, lower governmental quality indicates less adaptive capacity and thus more vulnerability, which might mean governmental quality is negatively related to adaptation aid.

3.3.4. ND-GAIN adaptive capacity

Similar to the WGIs, the ND-GAIN adaptive capacity sub-index (ND-GAIN, n.d.) also comprises a range of measures, reflecting both recipient merit and recipient need. For example, it captures infrastructure quality, a country's preparedness to cope with disasters, and engagement in international environmental conventions (ND-GAIN, n.d.). As such, despite the name, ND-GAIN adaptive capacity is also a measure of governmental quality. Higher values of the variable indicate *lower* adaptive capacity, meaning the higher a country's score, the less it is able to cope with the chal-

[2] The ND-GAIN also provides a variable capturing sensitivity to climate change. For a full list of indicators included in the ND-GAIN and its sub-indices, see ND-GAIN (2013). The exposure and sensitivity scores are strongly correlated and using one or the other variable does not substantively affect our results.

[3] As the annually reported CRI primarily indicates the impact of short-term weather variability, we also tested how the results change when we instead use a long-term (20 year) average of the CRI, which is more akin to vulnerability to disasters over the long-term. The results, not reported in this paper, are very similar to those produced using annual CRI data: an indication of the robustness of the models we report below.

lenges of climate change. When considering the variable as a measure of recipient need, we would expect a positive effect. On the other hand, the variable could again signal governmental quality and thus recipient merit, in which case we expect to see a negative relationship between higher values (lower governmental quality) and aid flows. The variable is again lagged by a year.

3.4. Measures of donor interest

To measure donor interests, we use various economic, historical, and diplomatic proxy variables. In contrast to the indicators discussed so far that focus entirely on recipient countries, the donor interest variables are inherently dyadic in nature.

3.4.1. Total exports

To capture economic interests of donors, we utilize data on bilateral trade flows, more specifically exports from the donor to the recipient country (total export of all commodities). These data are taken from the UN Comtrade database (United Nations, 2016) and are log-transformed as well as lagged by one year. The higher the exports of donor countries to recipients, the more it is in their interest to provide aid to the partner country (Younas, 2008). Thus, we expect a positive relationship between increased trade flows and adaptation aid.

3.4.2. Colonial ties

We expect colonial ties to play a role for (adaptation) aid allocation decisions, as donors want to sustain their influence over former colonies. As a result, former colonies are expected to receive more adaptation aid. Data on colonial ties between donors and recipients were retrieved from the Quality of Government Institute (Dahlberg, Holmberg, Rothstein, Khomenko, & Svensson, 2016). We added Timor-Leste, which was missing in this dataset, with Portugal being the former colonial power.

3.4.3. UN voting

Diplomatic relations and similarities in the preferences in world politics between donors and recipients are captured in the UN General Assembly Voting Data. We use the 2-category dyadic affinity scale ranging from −1 (least similar interests) to 1 (most similar interests) (Voeten, 2013). The data are lagged by one year. The more similar the preferences of donors and recipients in the international sphere, the more adaptation aid flows we expect to see.

3.4.4. Distance between partners

Donors have strategic interests in geographically close countries. We therefore include the distance between donor and recipient country. The minimum distance between all dyads in the dataset was calculated using the cshapes package of the R statistical computing environment (Gleditsch & Weidmann, 2010). We expect a negative relationship between distance and adaptation aid: the closer a recipient to the donor, the more adaptation aid it should receive from that donor.

3.5. Control variables

In addition, we include two control variables in the statistical models: total development aid and recipient countries' population.

3.5.1. Total development aid

Again using OECD Data (OECD, 2016), we coded total bilateral development aid flows from each donor to each recipient in a given year, using the same approach as for adaptation aid flows (without the per capita transformation). Due to the strongly skewed nature of the data, this variable is log-transformed. As the same institutions within donor countries distribute both development and adaptation aid, we expect the two to correlate highly. Therefore, we need to include total development aid in the models.

3.5.2. Population

As already mentioned, data on recipient countries' population is taken from the WDI (World Bank, 2016a). In the statistical models the data are lagged by one year and log-transformed. We include population for two reasons. On the one hand, larger countries are of greater geopolitical interest. On the other hand, population size influences the level of aid per capita, with smaller countries receiving more relatively more aid per capita. We thus expect a positive relationship at the selection stage (which determines whether a country receives adaptation aid), but a negative relationship at the allocation stage (which determines how much countries that do receive adaptation aid are allocated).

All the described variables are then compiled into a single dataset. Overall, there are 28 donor and 141 recipient countries in the dataset, and data on adaptation aid for five years from 2010 through 2015. 26 of the donors are in the dataset for the entire time period of the study, while two donors (Czechia and Iceland) only started to provide adaptation aid in 2011. Thus, overall the number of observations in the full dataset is 23,406. However, due to missing values in many of the covariates, the number of observations in the various models is somewhat lower than that figure. The authors will share the full dataset with interested readers upon request. Table 1 provides summary statistics for all variables (except the dummy variables LDCs, SIDS, African countries, and colonial ties).

3.6. Modelling strategy

Following the aid literature, we apply a two-stage Cragg Model (Clist, 2011a, 2011b; Manning, Duan, & Rogers, 1987), which allows a separation of aid allocation decisions into a selection and an allocation stage. According to Cragg's (1971) double-hurdle model, two hurdles must be crossed in order to report non-zero observed values, in our case adaptation aid. First, donors decide whether to provide aid to a recipient country, and second, they make allocation decisions on the amount of aid they distribute to the selected donors. The double-hurdle model is appropriate when the decisions to cross the two hurdles are made separately, i.e. are made at different points in time. Since decisions on aid recipients are usually made for an extended period of time, while projects are selected on a rolling basis, the double-hurdle model is appropriate when considering aid allocation decisions. The two stages are econometrically modelled separately, but the allocation stage must be interpreted conditionally on receiving aid at the selection stage (Clist, 2011a).

In addition, we include in both stages donor random effects, as a donor's adaptation aid allocations to many recipients in a given year cannot be regarded as entirely independent decisions. We also include year fixed effects to capture annual fluctuations in these early years of adaptation aid flows. The two stages of the Cragg Models are implemented in R using the lme4 package (Bates, Mächler, Bolker, & Walker, 2015).

The first stage of the models, presented in Table 2 below, models the decision whether recipient countries receive adaptation aid or not. Thus, in this stage the dependent variable is a simple binary decision taking on the value of 0 when adaptation aid is allocated, and zero otherwise. The formula for the model used in this first stage thus is

$$logit(\pi_{ij}) = \beta_0 + \beta_1 x_{1ij} + \ldots + \beta_{15} x_{15ij} + u_j$$

$$\pi_{ij} = P(y_{ij} = 1 | x_{1ij}, \ldots, x_{15ij}, u_j)$$

Table 1
Summary statistics for all numerical variables used in the statistical models.

	Mean	Median	St. Deviation	Minimum	Maximum	Valid N
Adaptation aid (mn. US$)	0.196	0	12.434	0	1687.75	19,098
ND-GAIN exposure	0.503	0.499	0.065	0.36	0.743	19,044
ND-GAIN vulnerability	0.49	0.482	0.094	0.293	0.751	19,044
SVCCI	36.559	35.895	7.018	24.73	61.28	16,284
CRI (inverted)	54.656	50.67	31.27	1	125	17,222
GDP per capita	4206.211	3147.575	3970.766	108.835	24831.68	19,182
WGI Index	−2.319	−2.278	3.161	−11.959	5.961	19,044
Eports (mn. US$)	612.175	14.801	5689.73	0	240000	18,749
UN voting	0.475	0.51	0.341	-1	1	19,044
Distance (km)	6887.42	6599.237	3811.553	0	18914.76	19,044
Population (mn.)	41.001	7.931	156.994	0.01	1357.38	19,126
Total aid (mn. US$)	20.364	0.148	119.306	0	6196	19,458

Table 2
Selection Stage.

	dv: principal adaptation aid/cap+						dv: principal and significant adaptation aid/cap+					
	(1)		(2)		(3)		(4)		(5)		(6)	
ND-GAIN exposure	3.171 ***	(0.518)					3.384 ***	(0.434)				
SVCCI			0.013 ***	(0.005)					0.003	(0.004)		
CRI					0.006 ***	(0.001)					0.005 ***	(0.001)
SIDS	0.399 ***	(0.102)	0.631 ***	(0.104)	0.604 ***	(0.101)	−0.011	(0.084)	0.246 ***	(0.086)	0.075	(0.085)
LDCs	0.063	(0.092)	0.259 ***	(0.095)	0.16 *	(0.094)	−0.131 *	(0.078)	−0.009	(0.080)	−0.028	(0.080)
Africa	−0.577 ***	(0.071)	−0.466 ***	(0.075)	−0.381 ***	(0.075)	−0.487 ***	(0.060)	−0.344 ***	(0.064)	−0.331 ***	(0.063)
GDP/cap+	1.563 ***	(0.425)	1.556 ***	(0.447)	2.012 ***	(0.447)	0.596 *	(0.346)	0.571 *	(0.354)	1.103 ***	(0.357)
GDP/cap^2+	−0.134 ***	(0.027)	−0.126 ***	(0.029)	−0.163 ***	(0.029)	−0.071 ***	(0.022)	−0.063 ***	(0.023)	−0.102 ***	(0.023)
WGI	0.829 ***	(0.068)	0.682 ***	(0.073)	0.792 ***	(0.071)	0.831 ***	(0.055)	0.731 ***	(0.059)	0.795 ***	(0.058)
ND-GAIN capacity	−0.343	(0.296)	−0.760 **	(0.303)	−0.515 *	(0.311)	0.195	(0.245)	−0.106	(0.252)	0.186	(0.258)
exports+	0.122 ***	(0.018)	0.099 ***	(0.019)	0.118 ***	(0.020)	0.097 ***	(0.014)	0.071 ***	(0.014)	0.094 ***	(0.015)
distance+	0.035	(0.039)	0.038	(0.044)	0.084 **	(0.042)	−0.039	(0.035)	−0.047	(0.042)	0.007	(0.037)
ex-colony	0.777 ***	(0.119)	0.802 ***	(0.126)	0.839 ***	(0.125)	0.786 ***	(0.128)	0.754 ***	(0.136)	0.819 ***	(0.134)
UN voting	−0.368 ***	(0.140)	−0.181	(0.164)	−0.485 ***	(0.156)	−0.465 ***	(0.120)	−0.238 *	(0.141)	−0.658 ***	(0.133)
total aid+	0.623 ***	(0.021)	0.645 ***	(0.022)	0.621 ***	(0.021)	0.887 ***	(0.020)	0.92 ***	(0.022)	0.898 ***	(0.021)
population+	0.107 ***	(0.025)	0.135 ***	(0.027)	0.078 ***	(0.029)	0.155 ***	(0.021)	0.181 ***	(0.023)	0.098 ***	(0.024)
(Intercept)	−12.728 ***	(1.776)	−12.299 ***	(1.878)	−13.118 ***	(1.876)	−8.243 ***	(1.452)	−7.079 ***	(1.509)	−8.436 ***	(1.508)
AIC	10,191.368		8975.793		9634.741		13,810.023		11,985.625		13,031.37	
BIC	10,359.413		9140.755		9801.12		13,978.068		12,150.587		13,197.749	
LogLikelihood	−5074.684		−4466.896		−4796.371		−6884.011		−5971.812		−6494.685	
Observations	22,074		19,060		20,390		22,074		19,060		20,390	
Groups (donors)	28		28		28		28		28		28	
random intercepts (donors)	0.953		1.120		0.900		1.973		2.224		1.917	

Notes: *p < .1, **p < .05, ***p < .01. +Logged values; yearly data lagged by one year; year dummies included but not shown; standard errors in parentheses.

$$u_j \sim \mathcal{N}(0, \sigma_u^2)$$

where y_{ij} represents the binary decision by donor j to allocate adaptation aid (1) or not (0) to recipient i, x_{1ij} to x_{15ij} are the independent variables observed for observation i on which donors j base their decision, and u_j are the donor random effects. The second stage models the amount of adaptation aid given to those countries that were selected in the first stage, i.e. for which $y1_{ij} = 1$. The formula is:

$$y2_{ij} = \beta_0 + \beta_1 x_{1ij} + \ldots + \beta_{15} x_{15ij} + u_j + e_{ij}$$

$$e_{ij} \sim \mathcal{N}(0, \sigma_e^2)$$

$$u_j \sim \mathcal{N}(0, \sigma_u^2)$$

where $y2_{ij}$ is the amount of adaptation aid committed by donor j to the recipient i selected in the first stage, x_{1ij} to x_{15ij} are the independent variables as above, u_j are the donor random effects, and e_{ij} are the remaining error terms.

4. Findings

4.1. Descriptive results

We start with a brief descriptive analysis of adaptation aid as reported by OECD (2016). Globally, adaptation aid is on the rise. In 2010, just under US$5 billion[4] of aid was marked as targeting adaptation (as a significant or principal objective); in 2015, this figure had risen to just over $10 billion. When looking at principal adaptation aid only, we observe about the same proportional increase: from $1.9 billion in 2010 to $2.8 billion in 2015. Yet, this is still far from a "balanced" distribution between mitigation and adaptation finance: between 2010 and 2015, $21.2 billion targeted adaptation only and $49.7 billion mitigation only, while $10.5 billion had both mitigation and adaptation objectives.

Adaptation aid is distributed unevenly, as shown in Fig. 1 and in Table A in the appendix. On average, every inhabitant of the devel-

[4] All figures are in constant 2013 US$.

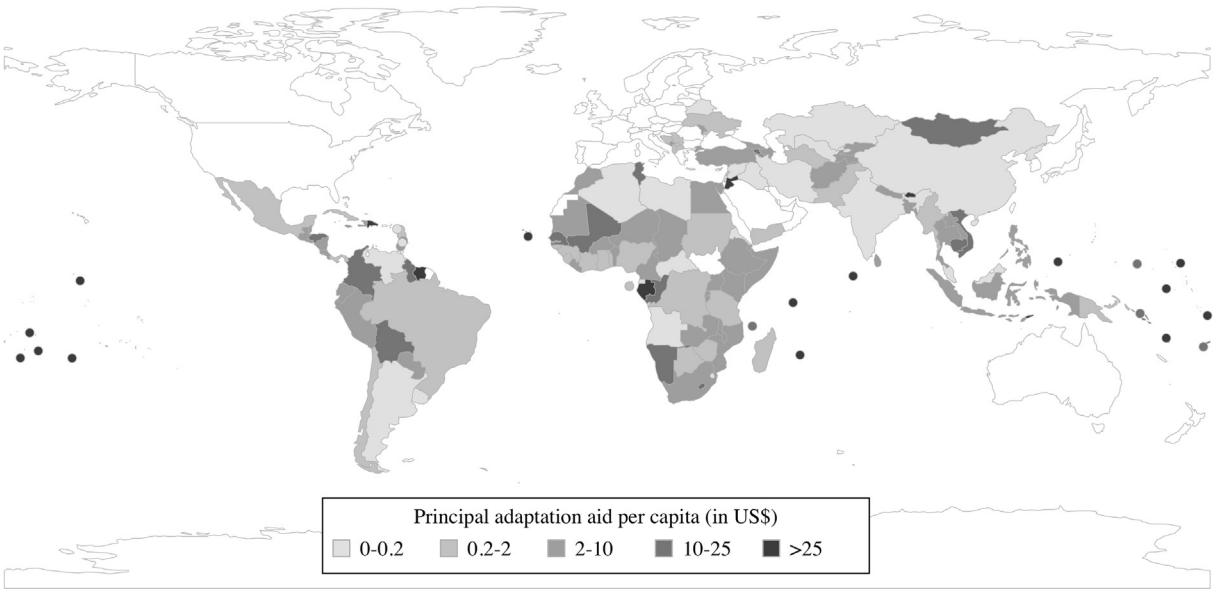

Fig. 1. Amount of principal adaptation aid flows to individual recipients by all donors form 2010 to 2015 (in US$ per capita).

oping world received $2.22 for projects with principal adaptation objective in the period from 2010 through 2015. Yet, per capita adaptation aid received varies considerably: from no support at all in four countries (Belarus, Equatorial Guinea, Iran, and Swaziland) to $2172 in Tuvalu and $2042 in Niue, two SIDS in the South Pacific.

SIDS in general tend to receive very high levels of adaptation support per capita: of the top ten per capita recipients of adaptation aid, nine are SIDS, with Gabon (ranked seventh at $136 per capita) the exception. On the other hand, some SIDS received very little per capita adaptation aid: for instance inhabitants of Guinea-Bissau received just 70 cents for adaptation projects (see Table A in the appendix).

In absolute terms, populous countries receive the bulk of adaptation aid. The five largest recipients—the Philippines, Vietnam, Bangladesh, Indonesia and Colombia—together account for almost exactly one third of all principal adaptation aid committed between 2010 and 2015 (see Table A in the appendix). Although only one of these is an LDC (Bangladesh) and none is in Africa, when considered together, the three particularly vulnerable country groups seem to be prioritised: SIDS, LDCs and African states are home to slightly less than 25 percent of the total population of the developing world, yet they received more than half of all adaptation aid. On a per capita level, inhabitants of these particularly vulnerable countries received $4.23 in adaptation aid, compared to $1.61 for inhabitants of other countries.

4.2. Regression results

In this section, we test the drivers of adaptation aid allocation more systematically, using proxies for recipient need—that is, vulnerability—, recipient merit, and donor interest. Our model includes two stages of aid allocation. Table 2 presents the results for the selection stage, i.e., the effect of drivers of adaptation aid on the *probability* of receiving any adaptation aid (regardless of the amount). Table 3 summarises the results for the allocation stage, i.e., the effect of drivers of adaptation aid on the *amount* of per capita adaptation aid committed to recipient countries (conditional on those countries receiving any adaptation aid at the selection stage). At both stages, we have three separate models since our three indices of physical vulnerability all try to capture the same concept, albeit using different data and methodologies. Consequently, we only include one of these variables at a time. Models 1 through 3 focus on principal adaptation aid only as the dependent variable, whereas models 4 through 6 include principal and (discounted) significant adaptation aid.[5,6]

The results are generally stable across the models as well as for both dependent variables under investigation. We discuss the results in the order of our hypotheses.

4.3. Physical vulnerability

H1a and H1b expect vulnerability to climate change, or recipient need, to drive adaptation aid allocation. Remember that vulnerability has two dimensions: physical vulnerability and adaptive capacity.

We have three measures of physical vulnerability: the ND-GAIN exposure index, the SVCCI, and the CRI. Panels a) to c) of Fig. 2 depict their effects at the selection stage, panels d) to f) at the allocation stage for principal adaptation aid only. In all three cases the trend is positive: more vulnerable countries are both more likely to be selected as adaptation aid recipients and tend to receive more adaptation aid per capita.

The ND-GAIN exposure index most strongly affects the allocation of adaptation aid. When comparing the least exposed countries (e.g. Moldova) to the most exposed countries

[5] As can be seen in the models, the number of observations varies between the models that use the same dependent variable (Models 1 through 3, and Models 4 through 6 in both Tables 2 and 3). This difference results from the different coverage of the three physical vulnerability measures (ND-GAIN exposure, SVCCI, and CRI). The ND-GAIN exposure variable covers the largest number of adaptation aid recipients; accordingly, the models with this measure have the largest sample size. In contrast, the CRI covers fewer adaptation aid recipients than the other measures, so the models with the CRI have the lowest number of observations. Because the number of observations varies between the models, a direct model comparison based on the likelihood (and therefore the AIC and the BIC) is not possible.

[6] As stated above, we apply a discount factor of 50% to significant adaptation aid contributions to construct the dependent variable used in models 4–6. This discount factor, while arbitrary, is used by a number of countries when reporting their adaptation (others discount at 40%, and some do not discount at all). As a sensitivity check we also constructed additional dependent variables: one applying a 40% discount factor to significant aid flows, and another not discounting significant adaptation aid at all. The results, not reported here, are very similar, regardless of the discount factor that is used. This is an indication of the robustness of our models.

Table 3
Allocation Stage.

	dv: principal adaptation aid/cap$^+$						dv: principal and significant adaptation aid/cap$^+$					
	(1)	(2)	(3)	(4)	(5)	(6)
ND-GAIN exposure	1.017 ***	(0.200)					0.813 ***	(0.126)				
SVCCI			0.009 ***	(0.002)					0.006 ***	(0.001)		
CRI					0.000	(0.000)					0.000	(0.000)
SIDS	0.173 ***	(0.042)	0.204 ***	(0.042)	0.260 ***	(0.037)	0.207 ***	(0.026)	0.256 ***	(0.026)	0.258 ***	(0.024)
LDCs	0.091 ***	(0.035)	0.101 ***	(0.036)	0.096 ***	(0.032)	0.092 ***	(0.022)	0.132 ***	(0.022)	0.105 ***	(0.020)
Africa	0.052 *	(0.028)	0.011	(0.029)	0.074 ***	(0.026)	−0.013	(0.017)	−0.015	(0.017)	0.013	(0.016)
GDP/cap$^+$	0.366 **	(0.176)	0.275	(0.181)	0.450 ***	(0.160)	0.341 ***	(0.102)	0.304 ***	(0.105)	0.444 ***	(0.095)
GDP/cap^2$^+$	−0.024 **	(0.011)	−0.017	(0.012)	−0.029 ***	(0.010)	−0.022 ***	(0.007)	−0.019 ***	(0.007)	−0.029 ***	(0.006)
WGI	−0.014	(0.028)	−0.010	(0.030)	0.014	(0.026)	0.036 **	(0.016)	0.029 *	(0.017)	0.046 ***	(0.015)
ND-GAIN capacity	−0.496 ***	(0.121)	−0.472 ***	(0.123)	−0.502 ***	(0.111)	−0.273 ***	(0.073)	−0.318 ***	(0.074)	−0.290 ***	(0.069)
exports$^+$	0.039 ***	(0.008)	0.035 ***	(0.008)	0.021 ***	(0.007)	0.034 ***	(0.005)	0.034 ***	(0.005)	0.023 ***	(0.004)
distance$^+$	0.015	(0.013)	0.010	(0.014)	0.009	(0.012)	0.003	(0.009)	0.003	(0.010)	0.004	(0.008)
ex-colony	−0.199 ***	(0.041)	−0.160 ***	(0.042)	−0.161 ***	(0.037)	−0.201 ***	(0.030)	−0.175 ***	(0.031)	−0.166 ***	(0.028)
UN Voting	0.009	(0.056)	0.069	(0.064)	0.050	(0.053)	0.038	(0.037)	0.043	(0.042)	0.030	(0.036)
total aid$^+$	0.103 ***	(0.008)	0.103 ***	(0.009)	0.094 ***	(0.008)	0.134 ***	(0.005)	0.130 ***	(0.005)	0.125 ***	(0.005)
population$^+$	−0.176 ***	(0.010)	−0.173 ***	(0.011)	−0.127 ***	(0.010)	−0.168 ***	(0.006)	−0.160 ***	(0.007)	−0.134 ***	(0.006)
(Intercept)	0.356	(0.741)	0.888	(0.761)	0.106	(0.678)	0.451	(0.428)	0.656	(0.439)	0.118	(0.402)
AIC	3627.759		3266.931		2920.563		6434.762		5628.095		5271.177	
BIC	3755.649		3392.575		3047.508		6579.075		5769.876		5414.586	
LogLikelihood	−1791.88		−1611.465		−1438.282		−3195.381		−2792.047		−2613.589	
Observations	2473		2233		2369		5217		4650		5007	
Groups (donors)	27		26		27		27		27		27	
random intercepts (donors)	0.041		0.040		0.027		0.060		0.051		0.052	

Notes: *p < .1, **p < .05, ***p < .01. +Logged values; yearly data lagged by one year; year dummies included but not shown; standard errors in parentheses.

(e.g. Maldives), we see that the predicted probability of receiving adaptation aid increases by more than 200% (from a predicted probability to receive aid of about 2.8% at the lowest ND-GAIN exposure levels, to 9.1% at the highest), while the predicted per capita adaptation aid increases more than fivefold, from 13 cents to 67 cents (see panels a) and d) of Fig. 2).

Similar but somewhat weaker results are obtained with the SVCCI, where the predicted probability of receiving adaptation aid increases by about 60% from the least to the most vulnerable countries, while the predicted per capita adaptation aid increases by more than 300%, from 14 cents to 61 cents (see panels b) and e) of Fig. 2). Note that the effect of the SVCCI loses its statistical significance at the selection stage when we include discounted significant adaptation aid (model 5 of Table 2).

Finally, the CRI significantly increases the probability of receiving adaptation aid almost by 100%, from 2.6% for the least to 5.1% for the most vulnerable countries, but does not influence the amount of per capita adaptation aid at the allocation stage (models 3 and 6 of Table 3 and panels c) and e) of Fig. 2).

Overall, these findings for physical vulnerability are quite robust and clearly indicate that donors allocate more adaptation aid to vulnerable countries, as H1a expected.

4.4. Adaptive capacity and good governance

How about adaptive capacity (H1b), the second dimension of vulnerability? Again, we have several measures, namely three dummy variables for the three groups of particularly vulnerable countries SIDS, LDCs and African countries; GDP per capita; the WGI index; and the ND-GAIN adaptive capacity index. As explained earlier, the last two measures also reflect good governance and hence recipient merit.

At the allocation stage we find strong evidence that SIDS, LDCs, and to a lesser degree African countries receive more adaptation aid per capita than countries outside of these groups. Model 1 of Table 3 thus predicts 87%, 44%, and 25% more adaptation aid for SIDS, LDCs, and African countries, respectively, compared to countries outside of these groups. This is in line with the descriptive evidence provided at the beginning of this section. However, the selection stage conveys a somewhat different image. Here, we find that SIDS are more likely to be selected in four of our six models and LDCs in two of six models (Table 2). African countries in contrast are *less* likely to be selected. Note though that this does not mean that African countries are selected less often than other countries *per se*,[7] but rather that they are selected less often than other countries that appear to have the same level of vulnerability (as measured by other covariates).

For GDP per capita, our second measure of adaptive capacity, we find a non-linear but mainly negative relationship at the selection stage: the probability of receiving adaptation aid decreases with higher GDP per capita, but only after GDP per capita reaches approximately $300. The left-hand panel of Fig. 3 shows this relationship in more detail for model 1 of Table 2. For the poorest countries in the dataset, the probability of being selected as recipients of adaptation aid in greater than 7%. This probability of selection falls to less than 5% when GDP per capita reaches $2000, and further drops to well under 3% at $5000. For the richest countries in the dataset the likelihood of selection falls to under 1%. These findings are mirrored across all models using both dependent variables under investigation. For the allocation stage the picture looks somewhat different (see right hand panel of Fig. 3). Here, the highest predicted values of adaptation aid (31 cents per capita) occur around income levels of $2400, while the very poorest countries

[7] African countries are selected in 860 out of 2518 times (34%) but represent only about 18% of the population in developing countries. LDCs are selected in 964 cases (38%) but represent only 15% of the population in developing countries, and SIDS in 363 cases (14%) but represent less than 1% of the population in developing countries. Also note that the categories are not mutually exclusive. When taken together, the three country groupings are selected in 1063 cases (42%) despite representing only about 24% of the population in developing countries.

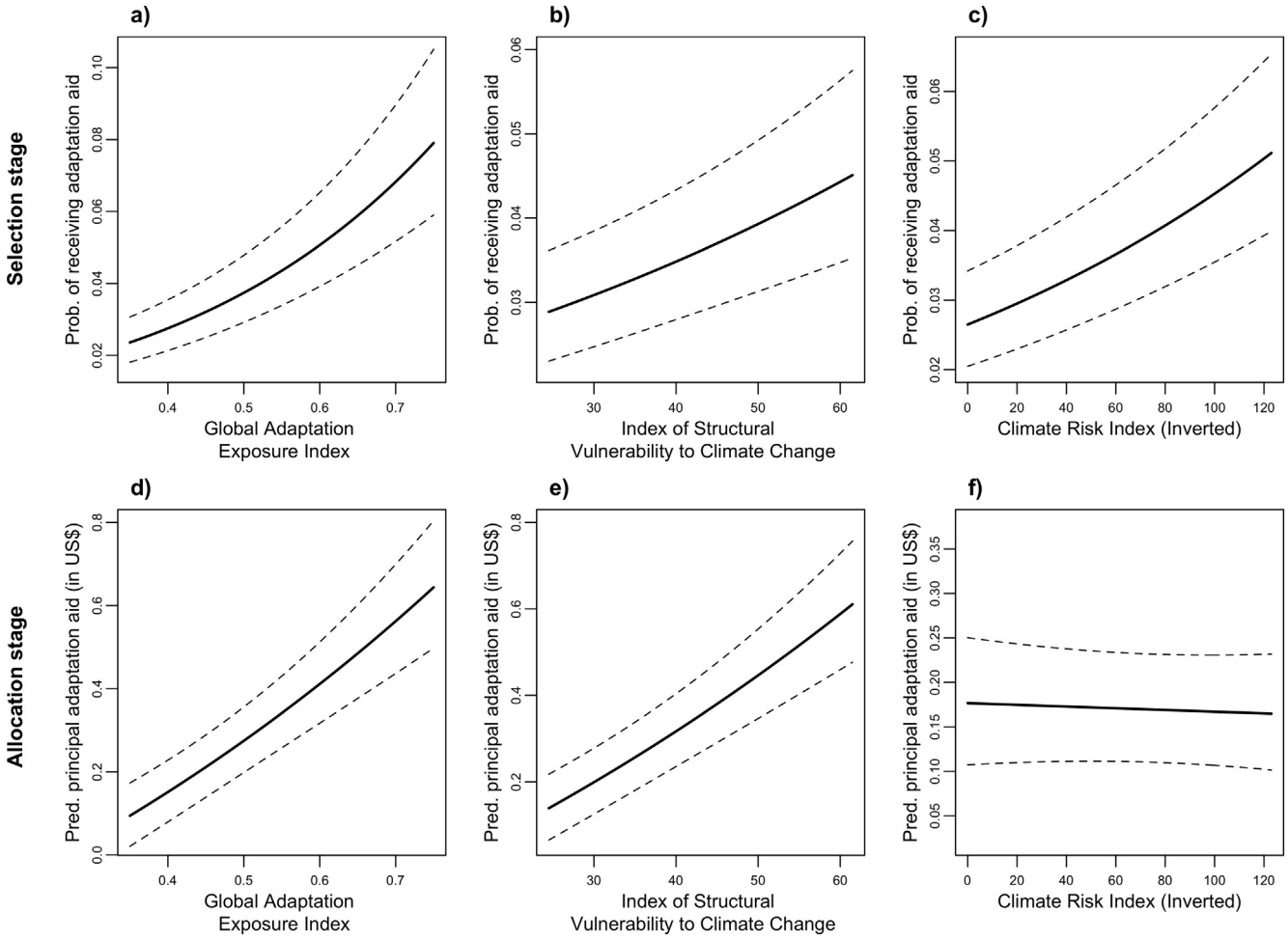

Fig. 2. Selection and allocation stage effects of the principal adaptation aid only models for the three variables used to capture physical exposure (including 90% confidence intervals).

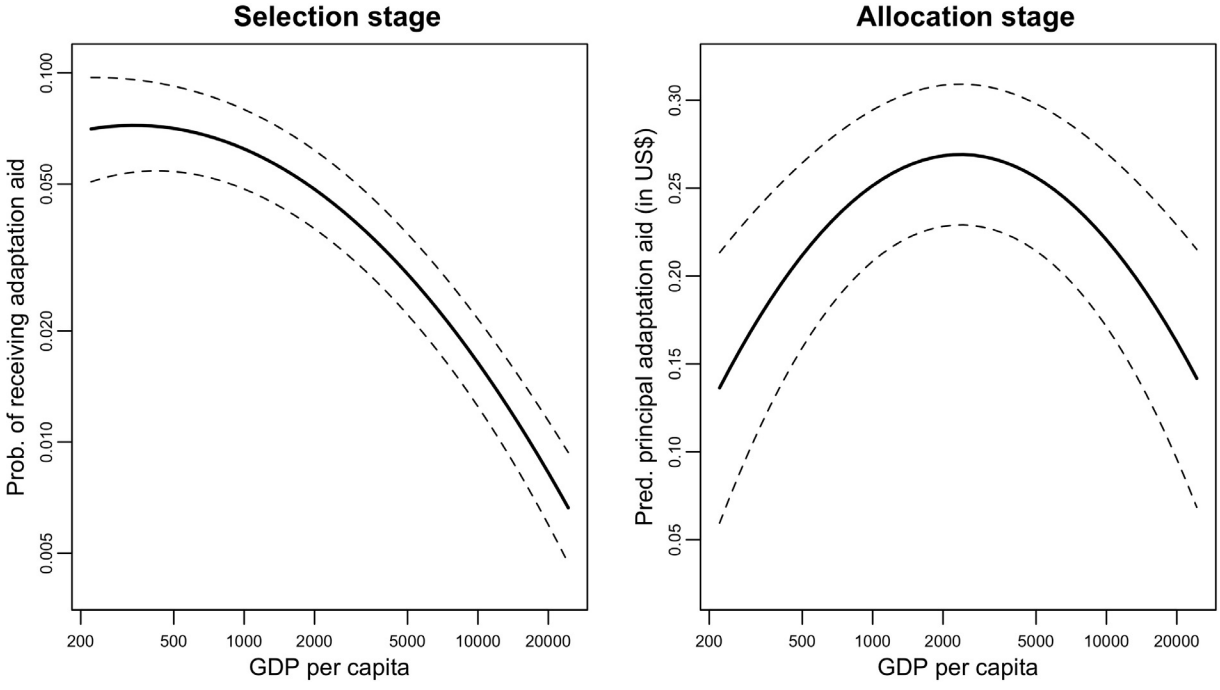

Fig. 3. Selection and allocation stage effects of the principal adaptation aid only models for GDP per capita (including 90% confidence intervals).

receive significantly less, at around 15 cents. Such low values of adaptation aid flows are then only observed again for the richest countries in the dataset. This could indicate that countries with very low GDP per capita values are perceived as unable to absorb large amounts of aid, and that as GDP per capita increases, greater adaptive capacity means higher levels of aid effectiveness.[8] However, these findings at the allocation stage are contingent on being selected in the first stage of adaptation aid allocation. As the poorest countries have a much higher probability of being selected than relatively richer developing countries, overall, the adaptation aid flows towards the former are much larger than those towards the latter. Again, these findings are similar across the models reported in Table 3.

Our third measure of adaptive capacity is governmental quality as measured by the composite WGI index. Note that the WGI index also reflects good governance and hence recipient merit. Better governed countries are substantially more likely to receive adaptation aid: From the lowest to the highest recorded value of the WGI index, the probability of receiving aid rises from almost zero to 15%—although better governed countries have better adaptive capacity and are hence less vulnerable to climate change. At the allocation stage, in contrast, we find no effect for the WGI index when considering principal adaptation aid only (models 1 through 3 of Table 3). When we also examine discounted significant adaptation aid (models 4 through 6 of Table 3), the WGI index has a positive and statistically significant effect on the amount of adaptation aid countries can expect (Table 3).

Finally, we also use the ND-GAIN adaptive capacity index. Note that the variable is coded such that higher values report higher vulnerability and hence lower adaptive capacity and worse governance. At the selection stage, adaptive capacity as measured by the ND-GAIN does not seem to influence adaptation aid allocation. The effect is only weakly statistically significant in models 2 and 3 of Table 2 (at the 5% and 10% level, respectively). At the allocation stage, however, we find a negative and consistently significant (at the 1% level) effect of the ND-GAIN adaptive capacity index. Model 1 of Table 3 predicts that the amount of adaptation aid drops from 51 cents per capita to just over 8 cents from the countries with the most adaptive capacity to those with the least adaptive capacity. In other words, countries that are better able to cope with climate change (higher adaptive capacity, lower values on the ND-GAIN capacity index) tend to receive more adaptation aid. These results—together with those for WGI (another measure of both adaptive capacity and recipient merit)—support the hypothesis that recipient merit drives adaptation aid allocation (H2) and suggest that this effect of recipient merit is stronger than that of adaptive capacity as measured by the WGI index and ND-GAIN adaptive capacity index.

Taken together, the findings for adaptive capacity and good governance provide evidence that donors are aware of the socio-economic dimension of vulnerability when making adaptation aid allocation decisions (H1b), but also take into account the absorptive capacity of recipient countries. Even if countries with better governmental quality are less vulnerable to climate change, they are presumably better able to put adaptation funding to good use and therefore tend to receive more support with adaptation (H2).

4.5. Donor interest

What about donor interests as measured by trade ties, colonial ties, voting patterns in the UN and geographic distance? Consistent with previous studies, we find that donors do take into account their own interests when allocating adaptation aid. This relationship is strongest in the case of economic interests; findings for geopolitical interests are mixed.

Trade ties are a strong driver of adaptation aid. All else being equal, countries that import more from a donor are both more likely to receive some adaptation aid and also receive larger amounts of adaptation aid. This is one of the strongest effects at both stages of adaptation aid allocation. At the selection stage, the predicted probabilities of receiving adaptation aid are close to zero at very low levels of trade, and then rise to around 13% at the very highest levels of trade. At the allocation stage, the amounts of adaptation aid flowing to recipients change from close to zero to almost 70 cents per capita.

Former colonies are also much more likely to receive some adaptation aid from their former colonial power: The predicted probability is about 3% higher for former colonies compared to other countries (model 1 of Table 2), which represents a percentage change in the probability of receiving adaptation aid of about 200%. Yet, once selected at the selection stage, former colonies receive much less adaptation aid per capita (83% less in model 1 of Table 2) from their past colonial powers than other countries. This might indicate that donors use the selection stage to signal to former colonies that they are important to them, but then do account for over-selection by sending lower amounts of adaptation aid.

Finally, there is no evidence to suggest that a country is more likely to receive adaptation aid, or to receive higher amounts of adaptation aid, if it votes the same way as the donor in the UN or is geographically closer to the donor. We suspect that this result reflects the fact that these last two variables are probably not very good in capturing the self-interests of donors. Yet the strong findings for exports and (to a lesser extent) colonial ties indicate the validity of H3.

4.6. Control variables

For our two control variable, total development aid and total population, the results indicate the expected effects.

Total development aid per capita is by far the strongest predictor of receiving adaptation aid at the selection stage. The predicted probability of receiving adaptation aid—according to Model 1 of Table 2—increases about threefold for countries that receive high levels of aid per capita compared to countries that receive limited to no development aid, from 6% for the latter to 19% for the former. At the allocation stage, total development aid is similarly the strongest predictor for the amount of adaptation aid a recipient country receives. Countries that receive high amounts of development aid receive about 250% more adaptation aid per capita than those that receive low amounts of overall development aid (45 cents compared to 13 cents per capita in adaptation aid).

This strong effect for total development aid may not be surprising. After all, adaptation aid is a *subset* of development aid. Furthermore, development in general tends to increase resilience. By providing adaptation aid and development aid jointly, donors may be providing a package of assistance that serves both adaptation and general development purposes. At the same time, this finding is potentially problematic insofar as donors have pledged new and additional resources to help developing countries deal with climate risks. That donors tend to provide adaptation aid to the same set of recipients to whom they provide regular development aid calls into question the additionality of resources, even if it is not possible to conclusively prove that funds are not additional.

Lastly, countries with larger populations are also more likely to receive adaptation aid, but then receive lower levels of per capita adaptation aid—as should be expected as very large recipients

[8] We would expect GDP per capita to have an effect on aid effectiveness that is independent of institutional quality because it means a country has more resources to contribute toward the implementation of development projects.

would need enormous amount of adaptation aid flows to match the contributions on a per capita level of smaller countries.

5. Conclusion

To what extent then is adaptation aid allocated to vulnerable countries, to well-governed countries or to countries of interest to the donor?

Our analysis suggests that physical vulnerability strongly influences both whether a country receives adaptation aid, and how much adaptation aid it receives. In contrast, adaptive capacity, the other dimension of vulnerability, does not seem to be a criterion for adaptation aid allocation. To some extent, this finding stands in contrast to previous research on adaptation aid, which concluded that vulnerability plays a small role if it is considered at all—although where studies found a relationship between adaptation funding and vulnerability, it was through physical vulnerability (Barrett, 2014; Betzold, 2015; Robinson & Dornan, 2016).

Our findings mirror, to some degree, the conclusions that poorer countries receive higher amounts of adaptation aid (when considering that they are much more likely to be chosen as recipients at the selection stage). The findings also reflect the results of the general development aid literature that recipient need matters.

Good governance or recipient merit also matters, as we have seen in the general development aid literature and the smaller adaptation aid literature (Dollar & Levin, 2006; Hoeffler & Outram, 2011; Robertsen et al., 2015; Younas, 2008). In fact, the findings for the two good governance indicators taken together are so strong that they match the explanatory power of the other two hypothesised effects. This suggests that the allocation decisions of donors are driven with a view to aid effectiveness. Well-governed countries, though better able to deal with climate change, are significantly more likely to receive support for adaptation, and receive more funds per capita, presumably because they are (perceived to be) better able to absorb and make good use of aid inflows.

Our results are mixed with respect to donor interests. Previous studies often conclude that donor interest play a stronger role than recipient need (see e.g. Alesina & Dollar, 2000; Berthélemy, 2006; McKinlay & Little, 1977). Our results, if anything, suggest the opposite. While we do find that exports are a very strong predictor of adaptation aid allocation, when considering the various components of vulnerability in our models collectively, they are at least as strong as donor interests in terms of driving adaptation aid allocation decisions. This indicates that adaptation aid is not driven by donor interests to the same extent as development aid; possibly because donors decisions are more directly bound to their past actions (which largely caused global warming), making them less likely to prioritise their own interests over recipient needs.

At the same time, adaptation aid to a significant degree follows the more established development aid flows. The strongest predictor of adaptation aid in our models is overall development aid. This is not surprising, for adaptation aid is a subset of development aid and the decision-making processes are closely linked. As these two forms of aid are mostly distributed via the same aid agencies, there seems to be a certain lock-in and cooperation with the same partners and partner countries, at least at these early stages of adaptation aid allocation. While there may be good reasons for this, given complementarities between development and adaptation aid, this does raise concerns about the additionality of resources. Adaptation aid and development assistance, while closely related, have different rationales: the latter is generally considered charity, while the former is considered a form of compensation for harm largely caused by industrialised countries under the polluter pays principle.

At this point it is sufficient to conclude that all three hypotheses on adaptation aid allocation are substantiated. Vulnerability (recipient need), good governance (recipient merit), and trade (donor interests) all play a role in determining who receives adaptation aid, and how much they are allocated. Which of the explanatory factors has the most impact on donors' allocation decisions remains unclear and might be a fruitful topic for further study, not least because the relative importance likely varies across donors.

Conflict of interests

The authors have no conflicts of interest.

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Appendix

Table A
Adaptation aid per recipient, 2010 through 2015.

	Adaptation aid per capita (US$)		Total adaptation aid (bn. US$)	
Recipient	Principal	Significant	Principal	Significant
Afghanistan	1.54	13.16	45.80	392.06
Albania	1.14	83.73	3.31	242.95
Algeria	0.07	0.65	2.64	24.26
Angola	0.12	0.48	2.75	10.86
Antigua and Barbuda	0.92	5.45	0.08	0.49
Argentina	0.10	0.32	4.09	13.55
Armenia	22.77	64.74	67.91	193.04
Azerbaijan	4.09	5.91	37.99	54.94
Bangladesh	3.93	2.71	611.23	421.63
Belarus	0.00	0.83	0.03	7.90
Belize	2.07	3.81	0.70	1.28
Benin	1.78	20.39	17.89	205.07
Bhutan	34.60	11.89	25.73	8.84
Bolivia	13.02	39.51	133.40	404.70
Bosnia and Herzegovina	0.01	7.74	0.02	29.63
Botswana	0.63	3.67	1.34	7.83
Brazil	0.21	1.40	41.95	282.71
Burkina Faso	6.53	17.08	108.55	283.80
Burundi	2.05	8.73	20.74	88.58
Cambodia	17.64	15.62	261.92	231.96
Cameroon	9.12	5.72	197.88	124.06
Cape Verde	75.33	53.06	37.79	26.62
Central African Republic	0.00	2.76	0.01	12.76
Chad	1.42	4.95	18.14	63.08
Chile	0.27	0.24	4.69	4.21
China	0.07	0.21	94.36	286.14
Colombia	4.81	2.73	225.45	127.81
Comoros	17.85	0.56	13.11	0.41
Congo (Brazzaville)	0.00	0.05	0.00	0.23
Congo (Kinshasa)	0.85	1.48	59.64	104.30
Cook Islands	155.79	1191.99	3.20	24.45
Costa Rica	2.94	14.43	13.71	67.15
Cote d'Ivoire	0.52	0.42	10.98	8.89
Cuba	1.07	2.35	12.09	26.60
Djibouti	8.10	14.63	6.91	12.49
Dominica	1.60	6.90	0.12	0.49
Dominican Republic	20.81	2.28	211.39	23.19
Ecuador	0.70	6.38	10.86	98.47
Egypt	2.88	1.90	246.90	163.17
El Salvador	1.95	32.60	11.83	197.97
Equatorial Guinea	0.53	1.72	0.41	1.33
Eritrea	0.16	0.34	0.80	1.65

(*continued on next page*)

Table A (*continued*)

Recipient	Adaptation aid per capita (US$)		Total adaptation aid (bn. US$)	
	Principal	Significant	Principal	Significant
Ethiopia	2.36	7.14	217.82	658.76
Fiji	13.05	18.71	11.41	16.35
Gabon	136.29	2.07	220.13	3.34
Gambia, The	2.74	4.96	4.95	8.98
Georgia	1.63	29.50	6.24	112.83
Ghana	1.10	5.78	28.05	147.65
Grenada	5.17	7.35	0.55	0.78
Guatemala	1.45	6.07	22.27	93.29
Guinea	0.67	1.57	7.86	18.30
Guinea-Bissau	0.70	4.51	1.20	7.74
Guyana	11.22	136.78	8.51	103.76
Haiti	2.75	12.80	28.35	131.73
Honduras	5.67	10.04	43.90	77.65
India	0.12	1.67	153.02	2115.29
Indonesia	2.25	1.82	558.37	451.81
Iran	0.00	0.05	0.00	3.73
Iraq	0.11	14.14	3.74	467.42
Jamaica	2.34	1.03	6.34	2.78
Jordan	15.11	49.21	105.55	343.86
Kazakhstan	0.01	0.07	0.15	1.12
Kenya	8.51	12.29	362.73	523.48
Kiribati	90.88	285.29	9.69	30.43
Korea, North	0.00	0.04	0.00	1.02
Kosovo	1.72	9.66	3.10	17.40
Kyrgyzstan	3.74	1.49	21.03	8.38
Laos	2.14	27.58	13.85	178.64
Lebanon	0.36	7.03	1.79	34.86
Lesotho	10.46	12.01	21.55	24.74
Liberia	1.73	18.80	7.25	78.72
Libya	0.00	0.20	0.02	1.25
Macedonia	1.17	19.82	2.43	41.01
Madagascar	0.91	3.01	20.36	67.20
Malawi	5.11	11.80	80.39	185.68
Malaysia	0.05	0.24	1.38	6.98
Maldives	38.99	11.05	15.00	4.25
Mali	6.32	22.90	102.01	369.50
Marshall Islands	69.12	92.55	3.64	4.87
Mauritania	9.98	8.54	37.75	32.31
Mauritius	81.96	1.59	102.92	2.00
Mexico	1.15	1.60	140.67	195.41
Micronesia	14.18	10.49	1.47	1.09
Moldova	3.25	8.73	11.57	31.08
Mongolia	15.74	28.12	44.26	79.06
Montenegro (FYROM)	8.30	16.30	5.15	10.12
Morocco	1.88	13.93	62.21	459.79
Mozambique	3.09	22.71	79.67	585.39
Myanmar	0.71	11.29	37.12	593.49
Namibia	5.69	39.96	13.06	91.76
Nauru	182.90	268.21	1.85	2.71
Nepal	1.81	11.34	49.89	312.06
Nicaragua	5.63	21.55	33.10	126.69
Niger	3.37	11.31	59.54	199.99
Nigeria	0.50	0.60	84.08	100.25
Niue	2042.42	11095.96	3.04	16.53
Pakistan	0.81	1.29	144.13	229.39
Palau	162.84	52.19	3.38	1.08
Panama	0.24	5.46	0.90	20.44
Papua New Guinea	1.37	7.82	9.82	56.00
Paraguay	2.46	7.20	15.69	45.92
Peru	7.95	19.46	239.93	587.20
Philippines	8.76	6.26	841.68	602.04
Rwanda	3.21	18.50	34.76	200.25
Samoa	66.20	98.76	12.51	18.66
Sao Tome and Principe	0.95	3.34	0.17	0.60
Senegal	9.05	11.59	125.03	160.11
Serbia	0.02	35.25	0.12	253.92
Seychelles	37.45	150.41	3.35	13.44
Sierra Leone	0.73	2.73	4.41	16.53
Solomon Islands	17.10	132.88	9.40	73.02
Somalia	3.31	9.65	33.25	96.93
South Africa	6.83	1.39	357.93	72.78
Sri Lanka	3.82	14.02	77.99	286.43
St Kitts and Nevis	0.02	0.00	0.00	0.00
St Lucia	2.82	0.00	0.51	0.00
St Vincent and the Grenadines	0.00	0.68	0.00	0.07
Sudan	0.20	2.58	7.65	97.36
Suriname	9.73	26.61	5.14	14.06
Swaziland	0.00	1.57	0.00	1.94
Syria	0.10	0.75	2.00	14.84
Tajikistan	2.07	3.23	16.41	25.66
Tanzania	1.49	12.25	72.71	597.22
Thailand	1.92	0.22	129.32	14.85
Timor-Leste	43.35	76.40	49.72	87.61
Togo	1.81	4.91	12.25	33.17
Tonga	66.04	102.55	6.92	10.75
Tunisia	15.54	42.79	167.53	461.22
Turkey	2.67	1.04	200.40	77.78
Turkmenistan	0.23	0.05	1.21	0.24
Tuvalu	2171.89	718.69	21.42	7.09
Uganda	4.38	10.00	155.40	354.61
Ukraine	0.13	0.54	6.10	24.43
Uruguay	0.08	1.25	0.28	4.26
Uzbekistan	0.13	0.47	3.80	14.12
Vanuatu	28.22	516.86	6.99	128.03
Venezuela	0.03	0.07	1.04	1.95
Vietnam	8.94	12.44	794.37	1105.67
Yemen	0.83	3.56	20.73	88.55
Zambia	4.48	17.12	66.31	253.72
Zimbabwe	0.74	7.42	10.81	108.32

Note: Figures are in 2013 constant US$ and represent total bilateral adaptation aid committed over the entire period 2010–2015 from all OECD DAC donors, as reported in OECD (2016).

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